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Multi-criteria Comparison of Electric Sport Utility Vehicles Using Proportional Spherical Fuzzy VIKOR Method

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Abstract

The burgeoning interest in Electric Vehicles (EVs) as sustainable alternatives to traditional combustion engine vehicles underscores a pivotal shift in automotive preferences worldwide. Amidst this transition, electric Sport Utility Vehicles (SUVs) have emerged as a compelling option, offering spacious interiors and eco-friendly mobility. However, the rapid proliferation of electric SUV models presents consumers with a complex decision-making landscape, necessitating robust Multicriteria Decision Making (MCDM) methodologies. In response, this study proposes a novel approach by extending the VIKOR method using Proportional Spherical Fuzzy Sets (PSFSs), accommodating the vagueness and imprecision inherent in decision-making processes. The literature review highlights a dearth of research specifically targeting electric SUV selection, emphasizing the novelty and significance of this study. Drawing upon recent advancements in fuzzy set theory, particularly PSFSs, the proposed methodology aims to provide a more intuitive and accurate means of evaluating electric SUV alternatives. By leveraging the flexibility and sensitivity of PSFSs, this method offers decision-makers a systematic framework to navigate the multifaceted criteria influencing electric SUV selection, encompassing factors such as driving range, charging infrastructure, performance, and price. Through a comprehensive evaluation process, this study aims to empower consumers with informed decision-making tools, facilitating the adoption of electric SUVs and contributing to a more sustainable automotive future. A comparative analysis with the Proportional Intuitionistic Fuzzy (PIF) CODAS method demonstrated the superiority of the proposed approach in terms of simplicity, computational efficiency, and flexibility in assigning membership degrees. Moreover, a sensitivity analysis highlighted the robustness of the proposed method against variations in expert weights, ensuring reliable decision-making outcomes.

Keywords: Proportional spherical fuzzy sets, VIKOR, CODAS, Electric vehicle, Sport utility vehicle.

1 | Introduction

As the global consciousness shifts towards sustainability, the allure of electric automobiles continues to intensify with each passing day. Beyond the sleek designs and futuristic aesthetics, their rising popularity stems from a convergence of factors. Environmental concerns drive the demand, with Electric Vehicles (EVs)

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offering a cleaner alternative to traditional gas-powered cars, significantly reducing greenhouse gas emissions and lessening the dependence on finite fossil fuels. Technological advancements have made EVs more accessible, with improved battery efficiency extending driving ranges and enhancing performance. Additionally, the expanding infrastructure of charging stations across urban landscapes alleviates range anxiety, bolstering consumer confidence in making the switch. Moreover, governmental incentives and regulations increasingly favor electric mobility, incentivizing consumers to embrace this paradigm shift. With each charge, electric automobiles not only redefine the driving experience but also represent a collective step towards a greener, more sustainable future.

In 2022, there was a surge in performance, setting new records in EV sales. With over 10 million EVs sold, they accounted for 14% of all new car purchases, a significant increase from 9% in 2021 and less than 5% in 2020. Consequently, the number of electric cars on roads worldwide exceeded 26 million in 2022, reflecting a remarkable 60% rise from the previous year [1]. By November 2023's conclusion, the United States achieved a milestone: annual sales of fully battery-powered vehicles surpassed 1 million for the first time. This marked a remarkable 50.7 percent year-over-year growth, with all EVs, including plug-in hybrids, experiencing a 30.6 percent increase compared to November 2022 [2].

An electric Sport Utility Vehicle (SUV) is a type of SUV that runs entirely or partially on electricity. Similar to traditional SUVs, electric SUVs typically offer spacious interiors, ample cargo space, and a higher ground clearance. The exponential growth and transformation of electric SUV models present customers with an unprecedented challenge in selecting the right vehicle amidst a rapidly evolving landscape. Over recent years, the electric SUV market has experienced an extraordinary pace of change, characterized by a continuous stream of new models boasting enhanced battery technology, extended driving ranges, and innovative features. Recent research conducted by transport & environment UK [3] reveals a notable surge in SUV sales within the UK, with an increase of 23% observed since 2022. Specifically, while the tally of newly registered SUVs amounted to 910,000 in 2022, this figure has now escalated by a third, reaching 1.12 million. This rapid innovation leads to a proliferation of choices that can overwhelm consumers, who must consider factors such as range, charging infrastructure, performance, and price when selecting. Moreover, the expanding variety of electric SUV offerings, ranging from compact crossovers to full-size luxury SUVs, further complicates the decision-making process. Amidst this dizzying array of options, consumers are faced with the dilemma of choosing the electric SUV that best aligns with their lifestyle, driving habits, and values. Despite the challenges, this rapid evolution underscores the industry's commitment to sustainability and innovation, driving forward a greener and more dynamic automotive future.

The decision to choose an electric SUV amidst a plethora of options represents a Multicriteria Decision Making (MCDM) problem due to several factors. MCDM involves making decisions in the presence of multiple, often conflicting, criteria or objectives. In the case of selecting an electric SUV, customers must consider various factors simultaneously, such as driving range, charging infrastructure availability, purchase price, operating costs, environmental impact, performance, safety features, and brand reputation, among others. These criteria may have different weights or priorities depending on individual preferences and circumstances. MCDM techniques aim to systematically evaluate and compare alternatives based on these criteria, helping decision-makers navigate complex decision landscapes and identify the most suitable option. Techniques such as the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Multi-Attribute Utility Theory (MAUT) are commonly used in MCDM to assist decision-makers in ranking alternatives and making informed choices. In the context of choosing an electric SUV, MCDM provides a structured framework for evaluating and prioritizing the diverse array of options available, considering the multiple criteria that influence the decision-making process. By systematically considering and weighing these criteria, MCDM helps customers navigate the complexity of the decision and select the electric SUV that best aligns with their preferences, needs, and constraints.

The decision to select an electric SUV is often fuzzy due to the subjective and imprecise nature of the criteria involved. Fuzzy MCDM methods are particularly suited to address such problems because they can

accommodate ambiguity, uncertainty, and vagueness in decision-making. In the context of selecting an electric SUV, many criteria may not have precisely defined boundaries or values. Fuzzy MCDM methods allow decision-makers to express their preferences and judgments in linguistic terms, such as "high," "medium," or "low," rather than requiring precise numerical values. This flexibility enables decision-makers to capture the inherent uncertainty and imprecision in the decision problem more effectively. Furthermore, the criteria involved in choosing an electric SUV are often interrelated and may exhibit complex relationships. Fuzzy MCDM methods can handle such interdependencies by modeling the fuzzy relationships between criteria and alternatives, providing a more comprehensive and realistic representation of the decision problem.

Nowadays, the SUV selection problem has become a difficult process for customers, as the design of vehicles can significantly change by the producers in a very short time. This process requires solving a fuzzy multicriteria decision model using accurate and consistent membership degrees as customers express their needs in vague and imprecise expressions. Hence, PSF-VIKOR is an excellent decision model for solving this problem.

The gap we tried to settle is the difficulty of assigning membership, non-membership, and hesitancy degrees in a fuzzy set extension. The difficulty of the assignment will be eliminated by using proportions between degrees rather than decimal numbers as degrees of membership. Thus, more accurate and consistent assignments can be made. Thus, our study will significantly contribute to the literature by reflecting the expert's thoughts more realistically and accurately in the decision model, thanks to the proportions between the degrees.

This study aims to provide a novel decision-making method that will allow linguistic assessments, be easy to use, and produce consistent and sensitive results in the selection problem of electric SUV alternatives. In this regard, the VIseKriterijumsa Optimizacija I Kompromisno Resenje (VIKOR) model will be extended using the Proportional Spherical Fuzzy Sets (PSFSs), which is one of the latest extensions of ordinary fuzzy sets. This will enable a more practical, consistent, and sensitive evaluation of performance evaluation of electric SUV alternatives.

The ever-expanding landscape of fuzzy set theory, from its inception with the study of Zadeh [4] to the myriads of extensions like intuitionistic fuzzy sets [5], Pythagorean fuzzy sets, Fermatean fuzzy sets [6–8], and beyond, reflects an ongoing effort to capture the nuances of human thought using increasingly complex parameterizations. However, the necessity for experts to assign precise decimal membership degrees, often with multiple decimal places, poses a significant challenge due to its inherent subjectivity and tediousness. To address this issue, a novel approach based on proportional relationships between parameters is proposed by Kahraman [9], leading to the development of Proportional Fuzzy Sets (PFSs). This innovative method offers a more intuitive and accurate means of determining membership, non-membership, and indecision degrees, relying on proportional judgments rather than direct decimal assignments. By leveraging relative proportions, experts can express their assessments more easily and accurately, thereby enhancing the applicability of fuzzy set theory in decision-making contexts. PFS not only simplifies the assignment process but also accommodates imprecise proportions, such as "around 2.5" or "between 3.5 and 4," through tailored arithmetic operations and aggregation operators. With its foundation in proportional judgments, PFS emerges as a promising paradigm for advancing fuzzy set theory toward greater precision and usability.

Spherical Fuzzy Sets have found a wide application area in literature [10], [11]. PSFSs, a special extension of PFSs proposed by Kahraman [12], offer a novel framework for representing vague and imprecise propositions, such as the statement "EVs are problematic in cold weather." In this paradigm, experts express their judgments not in precise decimal values but through proportional relationships between membership, non-membership, and indecision degrees. For example, if an expert assesses that the membership degree of the proposition is twice the indecision degree and the non-membership degree is five times the indecision degree, a PSFS representation can be derived accordingly. Here, the numerical values reflect the proportional relationships between the degrees of truthfulness, hesitancy, and falsity. By adopting PSFS, experts can

articulate their judgments more intuitively and accurately, enhancing the effectiveness of fuzzy set theory in modeling complex real world scenarios.

Various extensions of fuzzy sets have been integrated with many different MCDM models in the literature. The MCDM model to be utilized and extended by PSFSs in this study has been determined as VIKOR. The VIKOR method was initially conceived to address decision problems characterized by conflicting and noncommensurable criteria. This method operates under the assumption that a compromise is an acceptable approach for resolving conflicts, aiming to identify a solution closest to the ideal while evaluating alternatives across all established criteria. VIKOR assesses alternatives, ranking them to determine the compromise solution, which represents the closest approximation to the ideal. The name "VIKOR" emerged in 1998, derived from the Serbian phrase "VIKOR," meaning "multicriteria optimization and compromise solution" [13]. A paper in 2004 significantly contributed to the international recognition of the VIKOR method [14]. In the MCDM problem formulation, the objective is to identify the best compromise solution from a set of feasible alternatives, assessed based on a defined set of criterion functions represented by elements in the performance matrix.

In addition to proposing a novel decision-making method for evaluating electric SUV alternatives, this study conducts a thorough comparative analysis with one of the existing methodologies, Proportional Intuitionistic Fuzzy Combinative Distance-Based Assessment (PIF-CODAS), and explores the sensitivity of the proposed approach to variations in expert weights. These additional analyses enhance the study's comprehensiveness and underscore the practical relevance and effectiveness of the proposed approach in navigating the complex decision landscape of electric SUV selection.

The remainder of the document is structured as follows. In Section 2, a literature review is given. Section 3 presents the preliminaries of PSFSs. In Section 4, the VIKOR method is extended by using PSFSs, and this novel approach is given in steps. Section 5 presents the application of the new PSF-VIKOR method on performance evaluation of electric SUV alternatives together with comparative and sensitivity analyses. Finally, in Section 6, the paper concludes with discussions on findings and suggestions for future research directions.

2 | Literature Review

The decision problems related to EVs have been addressed in many different studies in the literature using MCDM methods. Among these studies, those integrated with fuzzy sets and published between the years 2022 and 2024 are summarized in *Table 1*, providing readers with information on the MCDM methods used, the fuzzy set extension employed, and the domain of the decision problem.

Table 1. Fuzzy MCDM studies in the literature related to EVs.

Author(s)	MCDM Method(s) Used	Extension of Fuzzy Sets	Application Area
Alamoodi et al. [15]	FDOSM	2-tuple linguistic T-spherical fuzzy sets	EV (electric bus) selection
Elomiya et al. [16]	AHP, SWARA	Ordinary fuzzy sets	EV charging station location selection
Golui et al. [17]	TOPSIS	Fermatean fuzzy sets	EV selection
Manirathinam et al. [18]	APPRESAL	Ordinary fuzzy sets	Performance and satisfaction assessment of e-scooters
Singh and Rizwanullah [19]	AHP, TOPSIS	Ordinary fuzzy sets	EV selection
Biswas et al. [20]	AROMAN	q-rung orthopair fuzzy sets	EV selection

Table 1. Continued.

Author(s)	MCDM Method(s) Used	Extension of Fuzzy Sets	Application Area
Aungkulanon [21]	AHP	Ordinary fuzzy sets	EV selection
Sadrani et al. [22]	BWM, RAFSI	Ordinary fuzzy sets	Charging strategy selection for electric buses
Yilmaz et al. [23]	AHP, MACBETH	Spherical fuzzy sets	EV charging station location selection
Wang et al. [24]	SWARA, MARCOS	Fuzzy rough sets	EV (Electric delivery vehicle) selection
Althaqafi [25]	TOPSIS	Ordinary fuzzy sets	Green supply chain management evaluation
Zhao et al. [26]	DEMATEL, MULTIMOORA	Ordinary fuzzy sets	EV solar charging station site selection
Tian et al. [27]	BWM, ORESTE	Hesitant intuitionistic fuzzy sets	EV selection
Koirala and Shabbiruddin [28]	COPRAS	Ordinary fuzzy sets	Sustainable battery supplier selection for battery swapping station
Qahtan et al. [29]	MARCOS	Pythagorean probabilistic hesitant fuzzy sets	Fuel supply system selection
Wei and Zhou [30]	BWM, VIKOR	Ordinary fuzzy sets	EV supplier selection
Ghose et al. [31]	COPRAS	Ordinary fuzzy sets	Material selection for solar EV
Qahtan et al. [32]	MULTIMOORA	Probabilistic hesitant fuzzy sets	Most suitable integrate sustainable transportation modeling approach selection
Panah et al. [33]	AHP	Hesitant fuzzy sets	Deployment of EV charging stations
Pradhan et al. [34]	COPRAS	Ordinary fuzzy sets	EV selection
Mall and Anbanandam [35]	AHP, VIKOR	Ordinary fuzzy sets	Selection of EV charging technology
Koirala et al. [36]	COPRAS	Ordinary fuzzy sets	Battery swapping station location selection

Abbreviations in *Table 1* in sequential order: entropy weight method, Fuzzy Decision by Opinion Score Method (FDOSM), Stepwise Weight Assessment Ratio Analysis (SWARA), Approach for Preference, Performance and Ranking Evaluation with SAtisfaction Level (APPRESAL), Alternative Ranking Order Method with Two-Step Normalization (AROMAN), Logarithmic Methodology of Additive Weights (LMAW), Ranking of Alternatives Through Functional Mapping of Criterion Sub-Intervals into A Single Interval (RAFSI), Best-Worst Method (BWM), Measuring Attractiveness by A Categorical Based Evaluation Technique (MACBETH), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Multiplicative Multi-Objective Optimization by Ratio Analysis (MULTIMOORA), Weighted Aggregated Sum Product Assessment (WASPAS), Organisation rangement et Synthe ' se de donne ' es relarionnelles (ORESTE),

Complex Proportional Assessment (COPRAS), Measurement Alternatives and Ranking According to Compromise Solution (MARCOS), Elimination and Choice Translating Reality (ELECTRE), Proximity Indexed Value (PIV).

In recent years, the latest MCDM research on EVs has prominently featured the use of AHP, COPRAS, TOPSIS, MULTIMOORA, and BWM methods, as evidenced in *Table 1*. This trend is consistent with usage patterns seen in the broader MCDM literature. Additionally, some less common methods have been utilized, such as APPRESAL, AROMAN, LMAW, FDOSM, and PIV. Since 2022, the VIKOR methodology has been employed in only two studies within this field. Given the success of VIKOR in other decision problem domains, its application in this context seems promising.

Furthermore, both studies have incorporated ordinary fuzzy sets, and no instances of more advanced extensions, such as PSFSs, have been observed. Upon closer examination of the studies summarized in Table 1, it's apparent that ordinary fuzzy sets are preferred the most, followed by the utilization of the hesitant fuzzy sets. This highlights a lack of utilization of three-parameter extensions, which typically account for the decision-maker's level of indeterminacy. Regarding the application areas of these studies, there's a focus on selecting the best EV alternative, followed by decisions related to charging station locations and supplier selection. However, to the authors' knowledge, no research specifically targeting electric SUVs has been identified, and this highlights the deficiency present in the literature in this field.

The main problem in these fuzzy EV studies (*Table 1*) is how the experts assign membership degrees. When we look at these studies, we see that the degrees are mostly assigned by the experts as a single-digit decimal number or sometimes as a two-digit decimal number. It is seen that three or more-digit degree assignments have not been realized in these studies. PFSs have provided a permanent solution to this problem.

The PFSs, one of the latest extensions of ordinary fuzzy sets integrated with VIKOR in this study, have been addressed in very few studies yet. These studies can be summarized as follows:

Kahraman [12] proposed the concept of PFSs and its extensions, such as Proportional Intuitionistic Fuzzy (PIF) sets, proportional pythagorean fuzzy sets, proportional picture fuzzy sets, and PSFSs, along with their arithmetic operations and aggregation operators. In the context of the car selection problem under consideration, they have noted minor alterations in the ranking of intuitionistic and spherical fuzzy sets. Kahraman [9] introduced the Proportional Picture Fuzzy Analytic Hierarchy Process (PPF-AHP) method and utilized it to evaluate alternative waste disposal sites. Through application, sensitivity analysis, and comparative studies, it is found that proportional picture fuzzy sets are readily adaptable to various problems and yield reliable results. Kahraman [39] added single-valued PIF sets to the CODAS approach to improve it. They compared the traditional fuzzy CODAS method with the suggested PIF-CODAS method. They tackled a cloud service provider selection problem to illustrate the efficacy of the suggested PIF-CODAS method. Kahraman [40] adapted the AHP method into the PIF-AHP method using PIF sets. They then contrasted the proposed PIF-AHP method with the interval-valued intuitionistic fuzzy AHP method found in existing literature. To demonstrate the effectiveness of the proposed PIF-AHP method, they addressed a wind turbine selection problem.

3 | Preliminaries: Proportional Spherical Fuzzy Sets

In this section, the preliminaries of PSFSs, as developed in the study by Kahraman [12], are presented to the readers. Considering the spherical fuzzy set $\tilde{S} = \{\langle x; \mu_{\tilde{S}}(x), \pi_{\tilde{S}}(x), \vartheta_{\tilde{S}}(x)\rangle | x \epsilon X\}$, the proportions between membership degree $(\mu_{\tilde{S}}(x))$, non-membership degree $(\vartheta_{\tilde{S}}(x))$, and hesitancy degree $(\pi_{\tilde{S}}(x))$ of an expert's judgment can be given as in *Eqs. (1)* and *(2)*.

$$\mu(x) = k_1 \pi_{\tilde{S}}(x), \tag{1}$$

and

$$\vartheta(x) = k_2 \pi_{\tilde{S}}(x), \tag{2}$$

where

$$\left(\pi_{\tilde{S}}(x)\right)^2 + \left(k_1\pi_{\tilde{S}}(x)\right)^2 + \left(k_2\pi_{\tilde{S}}(x)\right)^2 + \left(r_{\tilde{T}}(x)\right)^2 = 1. \tag{3}$$

The refusal degree can be determined using *Eq. (4)*.

$$r_{\tilde{S}}(x) = \sqrt{1 - \left(\left(\pi_{\tilde{S}}(x)\right)^2 + \left(k_1\pi_{\tilde{S}}(x)\right)^2 + \left(k_2\pi_{\tilde{S}}(x)\right)^2\right)}, \tag{4}$$

and

$$\pi_{\tilde{S}}(x) = \sqrt{\frac{1-\left(r_{\tilde{S}}(x)\right)^2}{1+(k_1)^2+(k_2)^2}}. \tag{5}$$

Consequently, each element in the set $\tilde{S}$ can be denoted by

$$\tilde{S} = \left\{ \langle x; k_1\sqrt{\frac{1-\left(r_{\tilde{S}}(x)\right)^2}{1+(k_1)^2+(k_2)^2}}, \sqrt{\frac{1-\left(r_{\tilde{S}}(x)\right)^2}{1+(k_1)^2+(k_2)^2}}, k_2\sqrt{\frac{1-\left(r_{\tilde{S}}(x)\right)^2}{1+(k_1)^2+(k_2)^2}} \rangle \,|\, x \in X \right\}. \tag{6}$$

When the refusal degree equals zero, *Eq. (6)* simplifies to

$$\tilde{S} = \left\{ \langle x; k_1\sqrt{\frac{1}{1+(k_1)^2+(k_2)^2}}, \sqrt{\frac{1}{1+(k_1)^2+(k_2)^2}}, k_2\sqrt{\frac{1}{1+(k_1)^2+(k_2)^2}} \rangle \,|\, x \in X \right\}. \tag{7}$$

Then, a PSFS can be expressed using *Eq. (8)*.

$$\tilde{S}_P = \{\langle x; r_{\tilde{S}}(x), k_{\pi 1}, k_{\pi 2}\rangle | x \in X\}. \tag{8}$$

Since PFSs use ratios between degrees, the values of these degrees can be obtained very precisely. For example, let's assume that the membership degree to be assigned by the expert is 5 times the refusal degree, the non-membership degree is 3 times the refusal degree, and the indecision degree is 2 times the refusal degree. In this case, the set will be sensitively obtained as SFS = (0.912871, 0.320256, 0.480384).

Consider two PSFSs denoted as $\tilde{A}$ and $\tilde{B}$. Addition and multiplication operations are defined according to *Eqs. (9)* and *(10)*, respectively.

$$\tilde{A} + \tilde{B} = \left(\begin{array}{c} x;\ k_{A1}\sqrt{\frac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} + k_{B1}\sqrt{\frac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}} - \\ k_{A1}\sqrt{\frac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} \times k_{B1}\sqrt{\frac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}}, \\ \sqrt{\frac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} \times \sqrt{\frac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}}, \\ k_{B2}\sqrt{\frac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}} \times k_{A2}\sqrt{\frac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} \Bigg| x \in X \end{array} \right). \tag{9}$$

$$\tilde{A} \times \tilde{B} = \left(\begin{array}{c} x; k_{A1}\sqrt{\dfrac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} \times k_{B1}\sqrt{\dfrac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}}, \\ \sqrt{\dfrac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} + \sqrt{\dfrac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}} - \\ \sqrt{\dfrac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} \times \sqrt{\dfrac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}}, \\ k_{B2}\sqrt{\dfrac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}} + k_{A2}\sqrt{\dfrac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} - \\ k_{B2}\sqrt{\dfrac{1-\left(r_{\tilde{B}}(x)\right)^2}{1+(k_{B1})^2+(k_{B2})^2}} \times k_{A2}\sqrt{\dfrac{1-\left(r_{\tilde{A}}(x)\right)^2}{1+(k_{A1})^2+(k_{A2})^2}} \Bigg| x \in X \end{array} \right). \quad \textbf{(10)}$$

If the refusal degree equals zero, then *Eq. (9)* and *Eq. (10)* simplify to

$$\tilde{A} + \tilde{B} = \left(\begin{array}{c} x;\ k_{A1}\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} + k_{B1}\sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}} - \\ k_{A1}\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} \times k_{B1}\sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}}, \\ \sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} \times \sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}}, \\ k_{B2}\sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}} \times k_{A2}\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} \Bigg| x \in X \end{array} \right). \quad \textbf{(11)}$$

$$\tilde{A} \times \tilde{B} = \left(\begin{array}{c} x; k_{A1}\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} \times k_{B1}\sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}}, \\ \sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} + \sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}} - \\ \sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} \times \sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}}, \\ k_{B2}\sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}} + k_{A2}\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} - \\ k_{B2}\sqrt{\frac{1}{1+(k_{B1})^2+(k_{B2})^2}} \times k_{A2}\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}} \Bigg| x \in X \end{array} \right). \quad \textbf{(12)}$$

Under the assumption of no refusal degree, multiplication operations by a constant and power are expressed as *Eqs. (13)* and *(14)*, respectively.

$$\lambda \cdot \tilde{A} = \left\langle \begin{array}{c} 1-\left(1-k_{A1}\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}}\right)^{\lambda}, \left(\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}}\right)^{\lambda} \\ , \left(k_{A2}\sqrt{\frac{1}{1+(k_{A1})^2+(k_{A2})^2}}\right)^{\lambda} \end{array} \right\rangle. \quad \textbf{(13)}$$

$$\tilde{A}^{\lambda} = < \left(k_{A1}\frac{1}{1+k_{A1}+k_{A2}}\right)^{\lambda}, 1-\left(1-\frac{1}{1+k_{A1}+k_{A2}}\right)^{\lambda}, 1-\left(1-k_{A2}\frac{1}{1+k_{A1}+k_{A2}}\right)^{\lambda}. \quad \textbf{(14)}$$

$$>$$

Let α_j $(j = 1,2, \dots, n)$ be a collection of PSFNs. The Proportional Spherical Fuzzy Weighted Averaging (PSFWA) operator is a mapping $PS^n \rightarrow PS$ such that

$$\mathrm{PSFWA}_w(\alpha_1, \alpha_2, \dots, \alpha_n) = \oplus_{j=1}^{n} (w_j \alpha_j), \tag{15}$$

where $w = (w_1, w_2, \dots, w_n)^T$ is the weight vector of α_j $(j = 1,2, \dots, n)$ and $w_j > 0, \sum_{j=1}^{n} w_j = 1$. Then

$$\mathrm{PSFWA}_w(\alpha_1, \alpha_2, \dots, \alpha_n) = \begin{pmatrix} 1 - \prod_{j=1}^{n} \left(1 - k_{1j}\sqrt{\frac{1}{1+(k_{1j})^2+(k_{2j})^2}}\right)^{w_j}, \\ \prod_{j=1}^{n} \left(\sqrt{\frac{1}{1+(k_{1j})^2+(k_{2j})^2}}\right)^{w_j}, \\ \prod_{j=1}^{n} \left(k_{2j}\sqrt{\frac{1}{1+(k_{1j})^2+(k_{2j})^2}}\right)^{w_j} \end{pmatrix}. \tag{16}$$

Let α_j $(j = 1,2, \dots, n)$ be a collection of PSFNs. The proportional spherical fuzzy weighted geometric (PSFWG) operator is a mapping $PS^n \rightarrow PS$ such that

$$\mathrm{PSFWG}_w(\alpha_1, \alpha_2, \dots, \alpha_n) = \otimes_{j=1}^{n} (\alpha_j)^{w_j}, \tag{17}$$

where $w = (w_1, w_2, \dots, w_n)^T$ is the weight vector of α_j $(j = 1,2, \dots, n)$ and $w_j > 0, \sum_{j=1}^{n} w_j = 1$. Then

$$\mathrm{PSFWG}_w(\alpha_1, \alpha_2, \dots, \alpha_n) = \begin{pmatrix} \prod_{j=1}^{n} \left(k_{1j}\sqrt{\frac{1}{1+(k_{1j})^2+(k_{2j})^2}}\right)^{w_j}, \\ 1 - \prod_{j=1}^{n} \left(1 - \sqrt{\frac{1}{1+(k_{1j})^2+(k_{2j})^2}}\right)^{w_j}, \quad 1 - \prod_{j=1}^{n} \left(1 - k_{2j}\sqrt{\frac{1}{1+(k_{1j})^2+(k_{2j})^2}}\right)^{w_j} \end{pmatrix}. \tag{18}$$

4 | Proportional Spherical Fuzzy VIKOR Method

The steps of the proposed Proportional Spherical Fuzzy VIKOR (PSF-VIKOR) method are presented below.

Step 1. Determine the criteria C_j $(j = 1, \dots, n)$ and the alternatives A_i $(i = 1, \dots, m)$. Discrimination among the criteria as Benefit (B) or Cost (C) should be taken into account.

Step 2. Determine k number of experts $(E_t, t = 1, \dots, k)$ who will evaluate the alternatives with respect to the considered criteria. The weights of the experts may vary depending on their experiences.

Step 3. Collect the linguistic evaluations of the experts to determine the importance of the criteria considered in *Table 2*.

Table 2. Linguistic evaluations of the experts for the criteria.

Experts	C1	C2	…	Cn
E_1	l_{C11}	l_{C12}	$\cdots$	l_{C1n}
E_2	l_{C21}	l_{C22}	$\cdots$	l_{C2n}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
E_k	l_{Ck1}	l_{Ck2}	$\cdots$	l_{Ckn}

Where l_{Ctj} is the linguistic evaluation of expert t for criterion j.

Step 4. Collect the decision matrices from each expert as in *Eq. (19)*.

$$\widetilde{D}_t = \begin{array}{c} \\ C1 \\ C2 \\ \dots \\ Cm \end{array} \begin{array}{c} \begin{array}{cccc} A1 & A2 & \dots & An \end{array} \\ \begin{bmatrix} l_{A11} & l_{A12} & \dots & l_{A1n} \\ l_{A21} & l_{A22} & \dots & l_{A2n} \\ \dots & \dots & \dots & \dots \\ l_{Am1} & l_{Am2} & \dots & l_{Amn} \end{bmatrix} \end{array}, \tag{19}$$

where l_{Aij} is the linguistic evaluation of expert t for alternative i with respect to criterion j.

Step 5. Transform the linguistic evaluations in *Table 2* into their corresponding PSF values using the scale given in *Table 3*. Then, aggregate the PSF values for the importance of the criteria using *Eq. (17)* or *Eq. (18)*. If an expert becomes hesitant between two successive linguistic terms in *Table 3*, they can assign any appropriate value.

Table 3. Linguistic PSF scale [12].

Linguistic Terms (l)	PSF Values
Certainly Low (CL)	(1,9)
Very Low (VL)	(2,8)
Low (L)	(3,7)
Below Average (BA)	(4,6)
Average (A)	(5,5)
Above Average (AA)	(6,4)
High (H)	(7,3)
Very High (VH)	(8,2)
Certainly High (CH)	(9,1)

Step 6. Transform the linguistic evaluations in the decision matrices into their corresponding PSF values using the scale in *Table 3*. Then, aggregate the decision matrices constructed by each expert using *Eq. (17)* or *Eq. (18)*.

Step 7. Compute the index S_i by using the spherical fuzzy numbers obtained as a result of the aggregation operation in *Step 6*.

$$\tilde{S}_i = \left(\oplus_{j=1}^{n} \left(\begin{array}{c} \sqrt{1 - \left(1 - \mu_{\tilde{w}_j}{}^2\right)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}}}, \\ \sqrt{\left(1 - \mu_{\tilde{w}_j}{}^2\right)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}} - \left(1 - \mu_{\tilde{w}_j}{}^2 - \pi_{\tilde{w}_j}{}^2\right)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}}}, \\ \left(v_{\tilde{w}_j}\right)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}} \end{array} \right) \right)^{1/5}, \quad i = 1, \dots, m, \tag{20}$$

where the sum of any two terms ($\widetilde{A}$ and $\widetilde{B}$) is computed by *Eq. (21)*.

$$\tilde{A} \oplus \tilde{B} = \left(\sqrt{\begin{array}{l} 1-\left(1-\mu_{\tilde{w}_j}{}^2\right)^{\frac{\left(f_j^*-f_{ij}\right)}{\left(f_j^*-f_j^-\right)}} + 1-\left(1-\mu_{\tilde{w}_j}{}^2\right)^{\frac{\left(f_{j+1}^*-f_{ij(+1)}\right)}{\left(f_{j+1}^*-f_{j+1}^-\right)}} - \\ \left(1-\left(1-\mu_{\tilde{w}_j}{}^2\right)^{\frac{\left(f_j^*-f_{ij}\right)}{\left(f_j^*-f_j^-\right)}}\right) \times \left(1-\left(1-\mu_{\tilde{w}_j}{}^2\right)^{\frac{\left(f_{j+1}^*-f_{ij(+1)}\right)}{\left(f_{j+1}^*-f_{j+1}^-\right)}}\right) \end{array}}, \right. \tag{21}$$

$$\sqrt{\left(1-\mu_{\tilde{w}_j}{}^2\right)^{\frac{\left(f_j^*-f_{ij}\right)}{\left(f_j^*-f_j^-\right)}} - \left(1-\mu_{\tilde{w}_j}{}^2-\pi_{\tilde{w}_j}{}^2\right)^{\frac{\left(f_j^*-f_{ij}\right)}{\left(f_j^*-f_j^-\right)}}} \times$$

$$\left. \sqrt{\left(1-\mu_{\tilde{w}_j}{}^2\right)^{\frac{\left(f_{j+1}^*-f_{i(j+1)}\right)}{\left(f_{j+1}^*-f_{j+1}^-\right)}} - \left(1-\mu_{\tilde{w}_j}{}^2-\pi_{\tilde{w}_j}{}^2\right)^{\frac{\left(f_{j+1}^*-f_{i(j+1)}\right)}{\left(f_{j+1}^*-f_{j+1}^-\right)}}}, \left(v_{\tilde{w}_j}\right)^{\frac{\left(f_j^*-f_{ij}\right)}{\left(f_j^*-f_j^-\right)}} \times \left(v_{\tilde{w}_j}\right)^{\frac{\left(f_{j+1}^*-f_{i(j+1)}\right)}{\left(f_{j+1}^*-f_{j+1}^-\right)}} \right).$$

For each criterion $j = 1, \ldots, n$ the best f_{ij} is specified as f_j^* and the worst f_{ij} as f_j^-. The f_j^* and f_j^- indexes are computed for the B criteria using *Eqs. (22)* and *(23)*.

$$f_j^* = \max\left(\left(k_{1ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} - \sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}}\right)^2 - \left(k_{2ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2,j}\right)^2}} - \sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}}\right)^2\right), i = 1, \ldots, m,\ j = 1, \ldots, n. \tag{22}$$

$$f_j^- = \min\left(\left(k_{1ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} - \sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}}\right)^2 - \left(k_{2ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2,j}\right)^2}} - \sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}}\right)^2\right), i = 1, \ldots, m,\ j = 1, \ldots, n. \tag{23}$$

For any value in the PSF decision matrix, the transformation is realized by *Eq. (24)*.

$$f_{ij} = \begin{pmatrix} k_{1ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \\ -\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \end{pmatrix}^2 - \begin{pmatrix} k_{2ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2,j}\right)^2}} \\ -\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \end{pmatrix}^2, i = 1, \ldots, m,\ j = 1, \ldots, n. \tag{24}$$

The f_j^* and f_j^- indexes are determined for the C criteria as in *Eqs. (25)* and *(26)*.

$$f_j^* = \min\left(\begin{pmatrix} k_{1ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \\ -\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \end{pmatrix}^2 - \begin{pmatrix} k_{2ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2,j}\right)^2}} \\ -\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \end{pmatrix}^2\right), i = 1, \ldots, m,\ j = 1, \ldots, n. \tag{25}$$

$$f_j^- = \max\left(\begin{pmatrix} k_{1ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \\ -\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \end{pmatrix}^2 - \begin{pmatrix} k_{2ij}\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2,j}\right)^2}} \\ -\sqrt{\frac{1}{1+\left(k_{1ij}\right)^2+\left(k_{2ij}\right)^2}} \end{pmatrix}^2\right), i = 1, \ldots, m,\ j = 1, \ldots, n. \tag{26}$$

Thus, *Eq. (20)* can be expressed by *Eq. (27)* briefly.

$$\tilde{S}_i = \left(\mu_{\oplus_i}, \pi_{\oplus_i}, v_{\oplus_i}\right), i = 1, \ldots, m. \tag{27}$$

The score value of $\tilde{S}_i$ is computed by *Eq. (28)*.

$$S_i = \left(\mu_{\oplus_i} - \pi_{\oplus_i}\right)^2 - \left(v_{\oplus_i} - \pi_{\oplus_i}\right)^2, i = 1, \dots, m. \tag{28}$$

Step 8. Compute the index R_i by using *Eqs. (22)-(26)* as in *Eq. (29)*.

$$R_i = \max_j \left(\left(\left(\sqrt{1 - (1 - \mu_{\tilde{w}}{}^2)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}}} - \sqrt{(1 - \mu_{\tilde{w}}{}^2)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}} - (1 - \mu_{\tilde{w}}{}^2 - \pi_{\tilde{w}}{}^2)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}}} \right)^2 - \left((v_{\tilde{w}})^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}} - \sqrt{(1 - \mu_{\tilde{w}}{}^2)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}} - (1 - \mu_{\tilde{w}}{}^2 - \pi_{\tilde{w}}{}^2)^{\frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}}} \right)^2 \right) \right), i = 1, \dots, m, j = 1, \dots, n. \tag{29}$$

Step 9. Compute the index Q_i as given by *Eq. (30)*.

$$Q_i = \tau \times [(S_i - S^*)/(S^- - S^*)] + (1 - \tau) \times [(R_i - R^*)/(R^- - R^*)],$$
$$S^* = \min_i S_i, S^- = \max_i S_i, R^* = \min_i R_i, R^- = \max_i R_i, \tag{30}$$

where τ is the weighting factor based on the experts' consensus.

Step 10. If the following two conditions are provided, the best alternative $\left(A^{(1)}\right)$ in the ranking compared to Q is considered a compromise solution.

Condition 1. Acceptable advantage.

$$Q\left(A^{(2)}\right) - Q\left(A^{(1)}\right) \geq \frac{1}{(J-1)}. \tag{31}$$

Here, J is the alternative number and $A^{(2)}$ is the second best alternative, according to Q.

Condition 2. Acceptable stability in decision-making.

Alternative $A^{(1)}$ ought to be ranked highest in the S and/or R rankings as well. This indicates that there is sufficient stability in the compromise solution when making decisions. The following list of workarounds is provided if any of these requirements are not satisfied:

I. In the event that just condition 2 is not satisfied, alternatives $A^{(1)}$ and $A^{(2)}$.

II. In the event that condition 1 is not satisfied, alternatives $A^{(1)}, A^{(2)}, \dots, A^{(M)}$.

Create a series of compromise solutions when the relationship is guaranteed by the highest M value, giving

$$A^{(M)}\ Q\left(A^{(2)}\right) - Q\left(A^{(1)}\right) \geq 1/(J-1). \tag{32}$$

5 | Performance Evaluation of Electric SUV Alternatives

In this study section, the novel PSF-VIKOR method developed in the previous section will be applied to the selection problem of the best electric SUV alternative. A total of 10 criteria and eight alternatives are considered in the analysis. The criteria were determined based on the consensus of three experts involved in the study, and their explanations are presented below:

I. Carbon footprint (C1): the total amount of greenhouse gas emissions, typically measured in units of carbon dioxide equivalent (CO2e), that are emitted over the entire lifecycle of the electric SUV.

II. Operating cost (C2): typically includes the expenses for electricity charging, maintenance, and potentially lower overall running Cs due to fewer moving parts, resulting in potential long-term savings compared to traditional internal combustion engine vehicles.

III. Potential incentives (C3): incentives such as tax credits, rebates, and reduced registration fees for purchasing electric SUVs.

IV. Operation noise (C4): generally lower compared to traditional internal combustion engine vehicles due to the absence of a combustion engine, resulting in a quieter driving experience characterized by minimal motor noise and reduced vibration. However, electric SUVs may produce some noise from components such as the tires, wind resistance, and ancillary systems.

V. Range (C5): the distance an electric SUV can travel on a single charge.

VI. Charging speed (C6): the rate at which the vehicle's battery can be replenished with electricity from an external power source, typically measured in kilowatts (kW) or miles of range added per hour of charging.

VII. Acceleration and power (C7): the ability to rapidly increase speed and deliver high performance, facilitated by the instant torque delivery of electric motors and the robust power output of its battery-driven propulsion system.

VIII. Cargo capacity (C8): the maximum volume or weight of goods, luggage, or other items that can be accommodated within the vehicle's storage area.

IX. Comfort and amenities (C9): the range of features and conveniences provided to occupants, including seating comfort, climate control systems, infotainment options, and additional amenities, enhance the overall passenger experience during travel.

X. Advanced safety technologies (C10): the innovative features and systems designed to mitigate collision risks, enhance driver awareness, and protect occupants, integrating cutting-edge sensors, cameras, and automated assistance functions for improved overall safety performance.

The alternatives are selected as Kia EV9, BMW iX, Skoda Enyaq, Tesla Model Y, Mercedes-Benz EQB, Genesis GV60, Hyundai Ioniq 5 N, and Volvo EX30. However, to ensure the confidentiality of companies, the alternatives have been randomly coded as A1, A2, …, A8. In the study, during the phase of creating decision matrices, opinions were sought, and linguistic assessments were obtained from three experts who work in an internationally operating company in Turkey, respectively as head of procurement (E1), data analyst (E2), and market analysis manager (E3). Considering the total work experience of the experts, their weights were taken as 0.40, 0.25, and 0.35, respectively.

The steps of the proposed PSF-VIKOR method are applied to the solution of the electric SUV selection problem in the following.

Step 1. The considered electric SUV criteria are determined as C1, C2, … C10, and alternatives are A1, A2, …, A8. The criteria A1, A2, and A4 are C criteria, whereas the rest are B criteria.

Step 2. The number of experts is three, whose weights are 0.40, 0.25, and 0.35, respectively.

Step 3. Based on the linguistic scale in *Table 2*, the experts assigned the most appropriate proportions for the importance of the considered criteria as in *Table 4*.

Table 4. PSF importances of the considered criteria.

Experts	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
E1	(6, 1)	(5, 1)	(4, 2)	(7, 3)	(8, 3)	(5, 1)	(3, 1)	(8, 3)	(6, 1)	(5, 3)
E2	(7, 3)	(4, 2)	(7, 2)	(6, 2)	(8, 2)	(4, 2)	(7, 2)	(4, 2)	(3, 2)	(8, 3)
E3	(4, 1)	(8, 1)	(6, 1)	(4, 1)	(3, 3)	(7, 1)	(5, 1)	(7, 1)	(8, 3)	(7, 1)

Step 4. The decision matrices from each expert are given in *Table 5*.

Table 5. PSF decision matrices.

Experts	Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
E1	A1	(3, 2)	(3, 2)	(4, 3)	(2, 1)	(4, 3)	(3, 2)	(4, 3)	(3, 2)	(2, 1)	(4, 3)
	A2	(5, 4)	(2, 1)	(2, 1)	(3, 2)	(2, 1)	(2, 1)	(5, 3)	(4, 3)	(3, 2)	(4, 2)
	A3	(2, 1)	(2, 1)	(3, 2)	(4, 2)	(3, 2)	(3, 2)	(3, 2)	(3, 1)	(2, 1)	(2, 1)
	A4	(4, 3)	(4, 3)	(3, 3)	(3, 2)	(4, 3)	(2, 1)	(4, 3)	(2, 1)	(3, 2)	(3, 2)
	A5	(5, 4)	(3, 2)	(4, 3)	(2, 1)	(3, 2)	(3, 1)	(2, 1)	(3, 2)	(4, 3)	(4, 2)
	A6	(6, 5)	(2, 1)	(2, 1)	(4, 3)	(3, 1)	(4, 3)	(3, 1)	(4, 3)	(4, 2)	(3, 3)
	A7	(2, 1)	(3, 2)	(3, 1)	(5, 3)	(4, 2)	(3, 2)	(3, 2)	(3, 2)	(3, 2)	(2, 1)
	A8	(5, 4)	(3, 2)	(4, 3)	(3, 2)	(4, 3)	(3, 2)	(2, 1)	(4, 1)	(3, 2)	(3, 2)
E2	A1	(4, 3)	(3, 2)	(3, 2)	(4, 3)	(2, 1)	(3, 3)	(3, 2)	(2, 1)	(3, 3)	(3, 2)
	A2	(3, 2)	(2, 1)	(2, 1)	(3, 2)	(4, 3)	(4, 3)	(4, 3)	(4, 3)	(3, 2)	(4, 3)
	A3	(3, 2)	(4, 3)	(4, 3)	(3, 2)	(4, 2)	(3, 2)	(3, 1)	(3, 2)	(4, 2)	(3, 2)
	A4	(4, 3)	(3, 2)	(3, 2)	(2, 1)	(4, 3)	(2, 1)	(2, 1)	(3, 2)	(2, 1)	(2, 1)
	A5	(2, 1)	(3, 2)	(4, 2)	(4, 3)	(3, 3)	(3, 1)	(4, 3)	(4, 3)	(4, 3)	(2, 1)
	A6	(3, 1)	(4, 3)	(2, 1)	(2, 2)	(2, 1)	(2, 1)	(4, 3)	(2, 2)	(2, 1)	(4, 3)
	A7	(4, 3)	(2, 1)	(3, 3)	(3, 2)	(3, 1)	(2, 1)	(3, 2)	(1, 1)	(4, 3)	(3, 2)
	A8	(4, 2)	(3, 2)	(3, 1)	(3, 2)	(4, 3)	(3, 2)	(3, 2)	(2, 1)	(4, 3)	(3, 1)
E3	A1	(4, 3)	(2, 1)	(3, 2)	(4, 3)	(4, 3)	(4, 3)	(4, 3)	(3, 2)	(4, 3)	(3, 2)
	A2	(2, 2)	(2, 1)	(2, 1)	(3, 2)	(2, 1)	(3, 1)	(3, 1)	(4, 2)	(2, 1)	(3, 1)
	A3	(3, 2)	(3, 3)	(4, 3)	(4, 2)	(3, 2)	(3, 2)	(3, 2)	(2, 2)	(2, 1)	(4, 3)
	A4	(4, 3)	(3, 2)	(2, 1)	(4, 3)	(4, 3)	(4, 3)	(3, 2)	(2, 1)	(3, 2)	(3, 2)
	A5	(2, 1)	(4, 3)	(3, 2)	(2, 1)	(3, 2)	(3, 2)	(4, 3)	(4, 3)	(2, 1)	(3, 2)
	A6	(4, 3)	(3, 2)	(3, 2)	(4, 3)	(3, 2)	(3, 2)	(2, 1)	(1, 1)	(3, 2)	(2, 1)
	A7	(2, 2)	(3, 2)	(2, 1)	(2, 1)	(3, 1)	(2, 1)	(2, 1)	(4, 3)	(4, 3)	(4, 3)
	A8	(4, 3)	(4, 2)	(3, 2)	(3, 2)	(3, 2)	(2, 2)	(4, 3)	(3, 2)	(2, 1)	(3, 2)

Step 5. Using *Eq. (18)*, we aggregated the PSF evaluations of the experts in *Table 4*. The aggregated results are given in *Table 6*.

Table 6. Aggregated PSF importances of the considered criteria.

Criteria	PSF Importances
C1	(0.9468, 0.1811, 0.2508)
C2	(0.9467, 0.1755, 0.2403)
C3	(0.9268, 0.1788, 0.3098)
C4	(0.9287, 0.1750, 0.3201)
C5	(0.8443, 0.1586, 0.4771)
C6	(0.9452, 0.1811, 0.2455)
C7	(0.9364, 0.2250, 0.2575)
C8	(0.9324, 0.1511, 0.3077)
C9	(0.9126, 0.1745, 0.3377)
C10	(0.9117, 0.1459, 0.3579)

Step 6. We aggregated the PSF decision matrices by *Eq. (18)* and obtained the results in *Table 7*.

Table 7. Aggregated PSF decision matrix.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.7913, 0.2254, 0.5676)	(0.8069, 0.3201, 0.4937)	(0.7948, 0.2396, 0.5568)	(0.7971, 0.2888, 0.5240)	(0.7924, 0.2554, 0.5493)	(0.7659, 0.2335, 0.5966)	(0.7888, 0.2145, 0.5755)	(0.8054, 0.3054, 0.5057)	(0.7715, 0.2963, 0.5560)	(0.7948, 0.2396, 0.5568)
A2	(0.7402, 0.2493, 0.6170)	(0.8165, 0.4082, 0.4082)	(0.8165, 0.4082, 0.4082)	(0.8018, 0.2673, 0.5345)	(0.8084, 0.3611, 0.4596)	(0.8379, 0.3230, 0.4273)	(0.8495, 0.2245, 0.4677)	(0.8143, 0.2039, 0.5405)	(0.8069, 0.3201, 0.4937)	(0.8605, 0.2432, 0.4384)
A3	(0.8076, 0.3273, 0.4876)	(0.7614, 0.2993, 0.5682)	(0.7913, 0.2254, 0.5676)	(0.8545, 0.2308, 0.4627)	(0.8190, 0.2553, 0.5117)	(0.8018, 0.2673, 0.5345)	(0.8263, 0.2760, 0.4848)	(0.7888, 0.3045, 0.5129)	(0.8302, 0.3656, 0.4154)	(0.8015, 0.3051, 0.5092)

Table 7. Continued.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A4	(0.7845, 0.1961, 0.5883)	(0.7948, 0.2396, 0.5568)	(0.7591, 0.3062, 0.5687)	(0.7993, 0.2825, 0.5265)	(0.7845, 0.1961, 0.5883)	(0.8051, 0.3413, 0.4788)	(0.7984, 0.2792, 0.5294)	(0.8128, 0.3758, 0.4427)	(0.8054, 0.3054, 0.5057)	(0.8054, 0.3054, 0.5057)
A5	(0.7982, 0.3174, 0.5029)	(0.7957, 0.2431, 0.5541)	(0.8119, 0.2272, 0.5352)	(0.8084, 0.3611, 0.4596)	(0.7718, 0.2580, 0.5789)	(0.8672, 0.2897, 0.3940)	(0.7971, 0.2888, 0.5240)	(0.7913, 0.2254, 0.5676)	(0.7955, 0.2779, 0.5326)	(0.8333, 0.2871, 0.4664)
A6	(0.8035, 0.1978, 0.5522)	(0.8032, 0.3115, 0.5031)	(0.8113, 0.3623, 0.4559)	(0.7532, 0.2329, 0.6095)	(0.8452, 0.3186, 0.4186)	(0.7984, 0.2792, 0.5294)	(0.8422, 0.3173, 0.4225)	(0.6766, 0.3874, 0.6059)	(0.8333, 0.2871, 0.4664)	(0.7550, 0.2900, 0.5818)
A7	(0.7530, 0.3339, 0.5579)	(0.8054, 0.3054, 0.5057)	(0.8151, 0.3245, 0.4613)	(0.8241, 0.2850, 0.4820)	(0.8917, 0.2693, 0.3590)	(0.8106, 0.3554, 0.4624)	(0.8069, 0.3201, 0.4937)	(0.7330, 0.3404, 0.5647)	(0.7913, 0.2254, 0.5676)	(0.8015, 0.3051, 0.5092)
A8	(0.8003, 0.1853, 0.5675)	(0.8260, 0.2505, 0.5023)	(0.8191, 0.2486, 0.5095)	(0.8018, 0.2673, 0.5345)	(0.7905, 0.2218, 0.5703)	(0.7516, 0.2911, 0.5859)	(0.8015, 0.3051, 0.5092)	(0.8594, 0.2936, 0.3973)	(0.8025, 0.3041, 0.5090)	(0.8263, 0.2760, 0.4848)

Step 7. We first computed the score value of each SF value in *Table 7*, and the results are given in *Table 8*.

Table 8. Score values of the aggregated decision matrix.

Score	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.2032	0.2069	0.2076	0.2030	0.2020	0.1516	0.1994	0.2099	0.1583	0.2076
A2	0.1057	0.1667	0.1667	0.2143	0.1903	0.2542	0.3315	0.2593	0.2069	0.3430
A3	0.2050	0.1413	0.2032	0.3353	0.2520	0.2143	0.2593	0.1911	0.2134	0.2047
A4	0.1923	0.2076	0.1362	0.2075	0.1923	0.1963	0.2070	0.1865	0.2099	0.2099
A5	0.1968	0.2086	0.2470	0.1903	0.1610	0.3226	0.2030	0.2032	0.2031	0.2661
A6	0.2412	0.2051	0.1929	0.1289	0.2674	0.2070	0.2644	0.0359	0.2661	0.1311
A7	0.1254	0.2099	0.2219	0.2518	0.3794	0.1957	0.2069	0.1038	0.2032	0.2047
A8	0.2322	0.2678	0.2574	0.2143	0.2020	0.1252	0.2047	0.3094	0.2064	0.2593

Then, we selected the min and max values, depending on whether they were B or C criteria, using *Eqs. (22)* and *(23)* or *Eqs. (25)* and *(26)*, and the results are given in *Table 9*.

Table 9. The best and worst values of each criterion.

Criteria	f_j^*	f_j^-
C1	0.1057	0.2412
C2	0.1413	0.2678
C3	0.2574	0.1362
C4	0.1289	0.3353
C5	0.3794	0.1610
C6	0.3226	0.1252
C7	0.3315	0.1994
C8	0.3094	0.0359
C9	0.2661	0.1583
C10	0.3430	0.1311

Next, the S_i values are calculated using *Eq. (28)* as given in *Table 10*.

Table 10. $\mathbf{S_i}$ **values.**

Alternatives	S_i Values
A1	0.8983
A2	0.7601
A3	0.9260
A4	0.8894
A5	0.8957
A6	0.9347
A7	0.9217
A8	0.9503

Step 8. We computed the index R_i using *Eq. (29)*. The results are shown in *Table 11*.

Table 11. $\mathbf{R_i}$ **values.**

Alternatives	R_i Values
A1	0.5193
A2	0.4108
A3	0.5470
A4	0.5424
A5	0.4933
A6	0.5859
A7	0.4806
A8	0.5905

Step 9. We computed the index Q_i using *Eq. (30)*, and the results are presented in *Table 12*.

Table 12. $\mathbf{Q_i}$ **values.**

Alternatives	Q_i Values
A1	0.6651
A2	0.0000
A3	0.8151
A4	0.7060
A5	0.5861
A6	0.9463
A7	0.6192
A8	1.0000

Here, τ value is taken as 0.5, which means equal importance for S_i and R_i values.

Step 10. Acceptable advantage*:* since $(0.5861 - 0.0000) \geq 1/(8-1)$ is provided, an acceptable advantage is satisfied, and alternative A2 is determined as the best alternative. Acceptable stability in decision-making: the compromise option has acceptable stability in decision-making, as indicated by the fact that Alternative A2 is ranked first in both S and R.

5.1 | Comparison Analysis with Proportional Intuitionistic Fuzzy CODAS

In this section, we compare the proposed PSF-VIKOR method with the PIF-CODAS method, which was proposed in the literature by Kahraman [39]. The same decision matrices (*Table 5*) and criteria weights (*Table 6*) used in PSF-VIKOR are used in the PIF-CODAS method. For the readers unfamiliar with the CODAS method, we present the PIF-CODAS method in the following, as presented by Kahraman [39].

Step 1. Let $\widetilde{D}$ be the matrix of PIF decisions. The numbers of criteria and options are n (i=1, 2, …, n) and m (j=1, 2, …, m), respectively. Experts e (ℓ=1,2, …, e) complete the decision matrix.

$$\widetilde{D}_{\ell}(l) = [l_{ij\ell}]_{n\times m} = \begin{bmatrix} l_{11\ell} & \cdots & l_{1m\ell} \\ \vdots & \ddots & \vdots \\ l_{n1\ell} & \cdots & l_{nm\ell} \end{bmatrix}, \ell=1,2, ..., e, \tag{33}$$

and

$$\widetilde{D}_{\ell}(\tilde{x}) = [\tilde{x}_{ij\ell}]_{n\times m} = \begin{bmatrix} \tilde{x}_{11\ell} & \cdots & \tilde{x}_{1m\ell} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{n1\ell} & \cdots & \tilde{x}_{nm\ell} \end{bmatrix}, \ell=1,2, \dots, e, \tag{34}$$

where the notation $\tilde{x}_{ij\ell} = (k_{1ij\ell}, k_{2ij\ell})$ represents the pertinent PIF performance score for criterion *j* of the alternative i provided by Expert ℓ.

Step 2. Aggregate the decision matrices using either *Eq. (33)* or *Eq. (34)*.

$$\mathrm{PIFWA}(\widetilde{D}_1, \widetilde{D}_2, \dots, \widetilde{D}_{\ell}, \dots, \widetilde{D}_e) = \begin{pmatrix} 1 - \prod_{\ell=1}^{e}\left(1 - k_{1ij\ell}\frac{1}{1+k_{1ij\ell}+k_{2ij\ell}}\right)^{w_\ell}, \\ \prod_{\ell=1}^{e}\left(k_{2ij\ell}\frac{1}{1+k_{1ij\ell}+k_{2ij\ell}}\right)^{w_\ell} \end{pmatrix} i = 1, \dots, m; j = 1, \dots, n. \tag{35}$$

By using *Eq. (33)*, *Table 13* is obtained.

Table 13. Aggregated decision matrix based on PIFWA.

Alternaes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.36, 0.50)	(0.30, 0.50)	(0.50, 0.35)	(0.32, 0.50)	(0.50, 0.34)	(0.48, 0.37)	(0.50, 0.36)	(0.50, 0.31)	(0.48, 0.33)	(0.50, 0.35)
A2	(0.38, 0.47)	(0.25, 0.50)	(0.50, 0.25)	(0.33, 0.50)	(0.50, 0.28)	(0.54, 0.26)	(0.56, 0.29)	(0.53, 0.34)	(0.50, 0.30)	(0.57, 0.27)
A3	(0.30, 0.50)	(0.33, 0.48)	(0.50, 0.36)	(0.30, 0.55)	(0.52, 0.32)	(0.50, 0.33)	(0.53, 0.29)	(0.51, 0.29)	(0.52, 0.26)	(0.50, 0.31)
A4	(0.38, 0.50)	(0.35, 0.50)	(0.47, 0.33)	(0.32, 0.50)	(0.50, 0.38)	(0.50, 0.29)	(0.50, 0.33)	(0.50, 0.27)	(0.50, 0.31)	(0.50, 0.31)
A5	(0.30, 0.50)	(0.35, 0.50)	(0.52, 0.34)	(0.28, 0.50)	(0.48, 0.35)	(0.57, 0.24)	(0.50, 0.32)	(0.50, 0.36)	(0.50, 0.33)	(0.53, 0.29)
A6	(0.33, 0.53)	(0.31, 0.50)	(0.50, 0.28)	(0.38, 0.48)	(0.54, 0.25)	(0.50, 0.33)	(0.54, 0.25)	(0.42, 0.37)	(0.53, 0.29)	(0.47, 0.34)
A7	(0.33, 0.47)	(0.31, 0.50)	(0.53, 0.26)	(0.30, 0.52)	(0.59, 0.23)	(0.50, 0.28)	(0.50, 0.30)	(0.46, 0.35)	(0.50, 0.36)	(0.50, 0.31)
	(0.36, 0.52)	(0.32, 0.53)	(0.53, 0.31)	(0.33, 0.50)	(0.50, 0.36)	(0.47, 0.36)	(0.50, 0.31)	(0.57, 0.24)	(0.50, 0.31)	(0.53, 0.29)

or

$$(\widetilde{D}_1, \widetilde{D}_2, \dots, \widetilde{D}_{\ell}, \dots, \widetilde{D}_e) = \begin{pmatrix} \prod_{\ell=1}^{e}\left(k_{1ij\ell}\frac{1}{1+k_{1ij\ell}+k_{2ij\ell}}\right)^{w_\ell}, \\ 1 - \prod_{\ell=1}^{e}\left(1 - k_{2ij\ell}\frac{1}{1+k_{1ij\ell}+k_{2ij\ell}}\right)^{w_\ell} \end{pmatrix} i = 1, \dots, m; j = 1, \dots, n. \tag{36}$$

By using *Eq. (34)*, *Table 14* is obtained.

Table 14. Aggregated decision matrix based on PIFWG.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.36, 0.50)	(0.31, 0.50)	(0.50, 0.35)	(0.33, 0.50)	(0.50, 0.35)	(0.48, 0.37)	(0.50, 0.36)	(0.50, 0.31)	(0.48, 0.34)	(0.50, 0.35)
A2	(0.38, 0.46)	(0.25, 0.50)	(0.50, 0.25)	(0.33, 0.50)	(0.50, 0.28)	(0.53, 0.27)	(0.56, 0.30)	(0.52, 0.35)	(0.50, 0.31)	(0.56, 0.28)
A3	(0.30, 0.50)	(0.35, 0.47)	(0.50, 0.36)	(0.30, 0.55)	(0.52, 0.32)	(0.50, 0.33)	(0.52, 0.30)	(0.50, 0.31)	(0.52, 0.26)	(0.50, 0.32)
A4	(0.38, 0.50)	(0.35, 0.50)	(0.47, 0.35)	(0.33, 0.50)	(0.50, 0.38)	(0.50, 0.30)	(0.50, 0.33)	(0.50, 0.27)	(0.50, 0.31)	(0.50, 0.31)
A5	(0.31, 0.50)	(0.35, 0.50)	(0.52, 0.34)	(0.28, 0.50)	(0.48, 0.36)	(0.56, 0.25)	(0.50, 0.33)	(0.50, 0.36)	(0.50, 0.33)	(0.53, 0.29)
A6	(0.35, 0.52)	(0.31, 0.50)	(0.50, 0.28)	(0.38, 0.47)	(0.54, 0.26)	(0.50, 0.33)	(0.54, 0.26)	(0.41, 0.37)	(0.53, 0.29)	(0.47, 0.36)
A7	(0.34, 0.46)	(0.31, 0.50)	(0.52, 0.28)	(0.31, 0.52)	(0.59, 0.24)	(0.50, 0.28)	(0.50, 0.31)	(0.45, 0.35)	(0.50, 0.36)	(0.50, 0.32)
A8	(0.36, 0.52)	(0.32, 0.52)	(0.52, 0.32)	(0.33, 0.50)	(0.50, 0.36)	(0.46, 0.36)	(0.50, 0.32)	(0.56, 0.25)	(0.50, 0.32)	(0.52, 0.30)

Step 3. Replace the proportions of each C criterion, if applicable, to compute the normalized decision matrix $\widetilde{D}_N$.

$$\widetilde{D}_N[\tilde{\tau}_{ij}] = \begin{bmatrix} \tilde{\tau}_{11} & \cdots & \tilde{\tau}_{1m} \\ \vdots & \ddots & \vdots \\ \tilde{\tau}_{n1} & \cdots & \tilde{\tau}_{nm} \end{bmatrix}, \tag{37}$$

where

$$\tilde{\tau}_{ij} = \begin{cases} \tilde{x}_{ij} = \tilde{\tau}_{ij}, & \text{if } j \in N_B, \\ \tilde{x}_{ij} = (k_{\pi 1ij}, k_{\pi 2ij}) \to \tilde{\tau}_{ij} = (k_{\pi 2ij}, k_{\pi 1ij}), & \text{if } j \in N_C, \end{cases} \tag{38}$$

where N_B and N_C denote the B and C criteria, respectively, and i=1, 2, …, n; j=1, 2, …, m.

Step 4. Determine the decision matrix that is weighted and normalized. *Eq. (37)*, which calculates the weighted normalized performance values, is used. The B criteria are represented in the first row of the equation, while the C criteria are shown in the second row.

$$\tilde{r}_{ij} = \begin{cases} \widetilde{w}_j \otimes \left(\dfrac{k_{\pi 1ij}}{1 + k_{\pi 1ij} + k_{\pi 2ij}}, \dfrac{k_{\pi 2ij}}{1 + k_{\pi 1ij} + k_{\pi 2ij}} \right), & \text{if } j \in N_B, \\ \widetilde{w}_j \otimes \left(\dfrac{k_{\pi 2ij}}{1 + k_{\pi 1ij} + k_{\pi 2ij}}, \dfrac{k_{\pi 1ij}}{1 + k_{\pi 1ij} + k_{\pi 2ij}} \right), & \text{if } j \in N_C, \end{cases} \tag{39}$$

where i=1, 2, …, n; j=1, 2, …, m; and $\widetilde{w}_j$ is the PIF weight of criterion j and $0 \leq \widetilde{w}_j \leq 1$.

The weighted normalized decision matrix is obtained in *Table 15* based on PIFWA.

Table 15. PIFWA-based weighted normalized decision matrix.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.25, 0.58)	(0.22, 0.57)	(0.34, 0.48)	(0.21, 0.61)	(0.31, 0.52)	(0.34, 0.47)	(0.33, 0.48)	(0.35, 0.44)	(0.32, 0.47)	(0.34, 0.49)
A2	(0.27, 0.56)	(0.18, 0.57)	(0.34, 0.40)	(0.22, 0.61)	(0.31, 0.48)	(0.38, 0.37)	(0.37, 0.41)	(0.36, 0.47)	(0.34, 0.44)	(0.38, 0.42)
A3	(0.21, 0.58)	(0.24, 0.55)	(0.34, 0.48)	(0.19, 0.65)	(0.32, 0.51)	(0.36, 0.44)	(0.35, 0.42)	(0.35, 0.43)	(0.35, 0.41)	(0.34, 0.46)
A4	(0.26, 0.58)	(0.25, 0.57)	(0.32, 0.46)	(0.21, 0.61)	(0.31, 0.55)	(0.36, 0.40)	(0.33, 0.45)	(0.35, 0.41)	(0.34, 0.45)	(0.34, 0.46)

Table 15. Continued.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A5	(0.21, 0.58)	(0.25, 0.57)	(0.35, 0.47)	(0.18, 0.61)	(0.30, 0.53)	(0.40, 0.36)	(0.33, 0.44)	(0.35, 0.48)	(0.34, 0.46)	(0.36, 0.44)
A6	(0.23, 0.61)	(0.22, 0.57)	(0.34, 0.42)	(0.25, 0.59)	(0.33, 0.46)	(0.36, 0.43)	(0.36, 0.39)	(0.29, 0.49)	(0.36, 0.44)	(0.32, 0.48)
A7	(0.23, 0.56)	(0.22, 0.57)	(0.36, 0.41)	(0.20, 0.63)	(0.36, 0.45)	(0.36, 0.39)	(0.33, 0.43)	(0.32, 0.47)	(0.34, 0.49)	(0.34, 0.46)
A8	(0.25, 0.60)	(0.23, 0.60)	(0.36, 0.44)	(0.22, 0.61)	(0.31, 0.54)	(0.33, 0.46)	(0.33, 0.43)	(0.40, 0.38)	(0.34, 0.45)	(0.36, 0.44)

The weighted normalized decision matrix is obtained in *Table 16* based on PIFWG.

Table 16. PIFWG-based weighted normalized decision matrix.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.25, 0.58)	(0.22, 0.57)	(0.34, 0.48)	(0.21, 0.61)	(0.31, 0.53)	(0.34, 0.47)	(0.33, 0.48)	(0.35, 0.45)	(0.32, 0.48)	(0.34, 0.49)
A2	(0.27, 0.55)	(0.18, 0.57)	(0.34, 0.40)	(0.22, 0.61)	(0.31, 0.48)	(0.38, 0.38)	(0.37, 0.43)	(0.36, 0.47)	(0.34, 0.45)	(0.38, 0.43)
A3	(0.21, 0.58)	(0.25, 0.55)	(0.34, 0.48)	(0.20, 0.65)	(0.32, 0.51)	(0.36, 0.44)	(0.35, 0.43)	(0.34, 0.44)	(0.35, 0.41)	(0.34, 0.46)
A4	(0.26, 0.58)	(0.25, 0.57)	(0.32, 0.47)	(0.22, 0.61)	(0.31, 0.55)	(0.36, 0.41)	(0.33, 0.45)	(0.35, 0.41)	(0.34, 0.45)	(0.34, 0.46)
A5	(0.22, 0.58)	(0.25, 0.57)	(0.35, 0.47)	(0.19, 0.61)	(0.30, 0.54)	(0.40, 0.37)	(0.33, 0.45)	(0.35, 0.48)	(0.34, 0.47)	(0.36, 0.44)
A6	(0.25, 0.60)	(0.23, 0.57)	(0.34, 0.42)	(0.25, 0.59)	(0.33, 0.47)	(0.36, 0.44)	(0.36, 0.40)	(0.28, 0.49)	(0.35, 0.44)	(0.32, 0.49)
A7	(0.23, 0.55)	(0.23, 0.57)	(0.35, 0.42)	(0.20, 0.63)	(0.36, 0.45)	(0.36, 0.40)	(0.33, 0.43)	(0.31, 0.48)	(0.34, 0.49)	(0.34, 0.46)
A8	(0.25, 0.60)	(0.23, 0.60)	(0.35, 0.45)	(0.22, 0.61)	(0.31, 0.54)	(0.33, 0.46)	(0.33, 0.44)	(0.39, 0.40)	(0.34, 0.46)	(0.35, 0.45)

Step 5. Determine the negative-ideal solution by computing the score values of the weighted normalized intuitionistic fuzzy numbers.

$$\mathrm{nis}_j = \min_{i=1,2,\ldots,n}\left(\frac{1-\vartheta_{\tilde{A}ij}}{2-\mu_{\tilde{A}ij}-\vartheta_{\tilde{A}ij}}\right), \text{for each } j; j=1, 2,\ldots, m. \quad (40)$$

$$\mathrm{NIS} = \left[\mathrm{nis}_j\right]_{1\times m}. \quad (41)$$

The score values of the weighted normalized intuitionistic fuzzy decision matrix are computed, and the negative-ideal solution is determined based on PIFWA, as in *Table 17*, and based on PIFWG, as in *Table 18*.

Table 17. Score values of the weighted normalized IF decision matrix and NISs based on PIFWA.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.3565	0.3519	0.4414	0.3307	0.4082	0.4475	0.4400	0.4593	0.4413	0.4366
A2	0.3766	0.3414	0.4767	0.3334	0.4300	0.5041	0.4835	0.4550	0.4558	0.4823
A3	0.3441	0.3697	0.4382	0.3018	0.4188	0.4661	0.4730	0.4699	0.4754	0.4513
A4	0.3602	0.3623	0.4406	0.3315	0.3946	0.4825	0.4547	0.4739	0.4526	0.4510
A5	0.3450	0.3618	0.4511	0.3232	0.3986	0.5184	0.4570	0.4416	0.4471	0.4653
A6	0.3390	0.3529	0.4677	0.3529	0.4476	0.4691	0.4909	0.4190	0.4668	0.4321
A7	0.3646	0.3538	0.4798	0.3173	0.4657	0.4851	0.4633	0.4361	0.4350	0.4513
A8	0.3481	0.3427	0.4638	0.3334	0.4004	0.4490	0.4603	0.5057	0.4525	0.4640

Table 18. Score values of the weighted normalized IF decision matrix and NISs based on PIFWG.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.3567	0.3527	0.4410	0.3323	0.4056	0.4458	0.4397	0.4581	0.4361	0.4363
A2	0.3791	0.3414	0.4767	0.3334	0.4277	0.4990	0.4779	0.4528	0.4544	0.4776
A3	0.3449	0.3740	0.4378	0.3029	0.4180	0.4661	0.4689	0.4591	0.4747	0.4487
A4	0.3602	0.3625	0.4350	0.3325	0.3946	0.4796	0.4526	0.4728	0.4515	0.4499
A5	0.3474	0.3620	0.4496	0.3243	0.3969	0.5136	0.4538	0.4413	0.4440	0.4638
A6	0.3447	0.3542	0.4664	0.3546	0.4436	0.4670	0.4857	0.4158	0.4653	0.4262
A7	0.3689	0.3545	0.4706	0.3186	0.4640	0.4837	0.4619	0.4330	0.4346	0.4487
A8	0.3500	0.3441	0.4583	0.3334	0.4001	0.4469	0.4578	0.4970	0.4504	0.4599

Step 6. Determine each alternative's Euclidean (E) and Taxicab (T) distances from the negative-ideal solution. While *Eq. (41)* provides the T distance for each option, *Eq. (40)* provides the E distance.

$$E_i = \sqrt{\sum_{j=1}^{m}\left(\frac{1-\vartheta_{\tilde{A}ij}}{2-\mu_{\tilde{A}ij}-\vartheta_{\tilde{A}ij}} - nis_j\right)^2}, i = 1, 2, \dots, n. \quad (42)$$

$$T_i = \sum_{j=1}^{m}\left|\frac{1-\vartheta_{\tilde{A}ij}}{2-\mu_{\tilde{A}ij}-\vartheta_{\tilde{A}ij}} - nis_j\right|, i=1, 2,..., n. \quad (43)$$

Table 19 displays the E and T distances based on PIFWA and PIFWG.

Table 19. Euclidean (E) and Taxicab (T) distances.

PIFWG		PIFWG	
E	T	E	T
0.0560	0.1247	0.0565	0.1235
0.1204	0.3502	0.1167	0.3391
0.0863	0.2197	0.0828	0.2143
0.0830	0.2153	0.0834	0.2102
0.0904	0.2205	0.0897	0.2158
0.1024	0.2493	0.0986	0.2427
0.1022	0.2631	0.0991	0.2577
0.1050	0.2312	0.0992	0.2168

Step 7. Construct the relative assessment matrix, R.

$$R = [h_{ik}]_{n\times n}. \quad (44)$$

$$h_{ik} = (E_i - E_k) + \psi(E_i - E_k) \times (T_i - T_k), \quad (45)$$

where $k \in \{1,2, \dots, n\}$ and ψ is a threshold function that establishes if the alternative distances between i and k differ by enough in Euclidean distance to account for the differences in T distances between them.

$$\psi(x) = \begin{cases} 1, & \text{if } |x| \geq \varphi, \\ 0, & \text{if } |x| < \varphi, \end{cases} \quad (46)$$

where φ is the expert-set threshold parameter. This parameter is taken as 0.03.

The relative assessment matrix, R, is computed with respect to PIFWA and PIFWG, as in *Table 20*.

Table 20. Matrix for relative assessment based on PIFWG and PIFWA.

PIFWA				PIFWG			
Comparison	$\mathbf{E_i - E_k}$	$\mathbf{T_i - T_k}$	$\mathbf{h_{ik}}$	**Comparison**	$\mathbf{E_i - E_k}$	$\mathbf{T_i - T_k}$	$\mathbf{h_{ik}}$
A1-A2	-0.0644	-0.2254	-0.2898	A1-A2	-0.0602	-0.2156	-0.2758
A1-A3	-0.0303	-0.0950	-0.1253	A1-A3	-0.0264	-0.0907	-0.0264
A1-A4	-0.0271	-0.0906	-0.0271	A1-A4	-0.0269	-0.0867	-0.0269
A1-A5	-0.0344	-0.0958	-0.1302	A1-A5	-0.0332	-0.0923	-0.1256
A1-A6	-0.0464	-0.1246	-0.1710	A1-A6	-0.0421	-0.1192	-0.1613
A1-A7	-0.0462	-0.1384	-0.1845	A1-A7	-0.0426	-0.1342	-0.1768
A1-A8	-0.0491	-0.1064	-0.1555	A1-A8	-0.0427	-0.0933	-0.1360
A2-A3	0.0341	0.1305	0.1645	A2-A3	0.0339	0.1248	0.1587
A2-A4	0.0373	0.1349	0.1722	A2-A4	0.0333	0.1288	0.1621
A2-A5	0.0300	0.1297	0.1597	A2-A5	0.0270	0.1232	0.0270
A2-A6	0.0180	0.1009	0.0180	A2-A6	0.0181	0.0964	0.0181
A2-A7	0.0182	0.0871	0.0182	A2-A7	0.0176	0.0814	0.0176
A2-A8	0.0154	0.1190	0.0154	A2-A8	0.0175	0.1222	0.0175
A3-A4	0.0033	0.0044	0.0033	A3-A4	-0.0006	0.0040	-0.0006
A3-A5	-0.0041	-0.0008	-0.0041	A3-A5	-0.0069	-0.0016	-0.0069
A3-A6	-0.0161	-0.0296	-0.0161	A3-A6	-0.0158	-0.0284	-0.0158
A3-A7	-0.0159	-0.0434	-0.0159	A3-A7	-0.0163	-0.0435	-0.0163
A3-A8	-0.0187	-0.0115	-0.0187	A3-A8	-0.0164	-0.0026	-0.0164
A4-A5	-0.0073	-0.0052	-0.0073	A4-A5	-0.0063	-0.0056	-0.0063
A4-A6	-0.0193	-0.0340	-0.0193	A4-A6	-0.0152	-0.0324	-0.0152
A4-A7	-0.0191	-0.0478	-0.0191	A4-A7	-0.0157	-0.0475	-0.0157
A4-A8	-0.0220	-0.0159	-0.0220	A4-A8	-0.0158	-0.0066	-0.0158
A5-A6	-0.0120	-0.0288	-0.0120	A5-A6	-0.0089	-0.0268	-0.0089
A5-A7	-0.0118	-0.0426	-0.0118	A5-A7	-0.0094	-0.0419	-0.0094
A5-A8	-0.0147	-0.0107	-0.0147	A5-A8	-0.0095	-0.0010	-0.0095
A6-A7	0.0002	-0.0138	0.0002	A6-A7	-0.0005	-0.0150	-0.0005
A6-A8	-0.0026	0.0181	-0.0026	A6-A8	-0.0006	0.0258	-0.0006
A7-A8	-0.0029	0.0319	-0.0029	A7-A8	-0.0001	0.0409	-0.0001

Step 8. Determine each alternative's assessment score, H_i:

$$H_i = \sum_{k=1}^{n} h_{ik}. \tag{47}$$

The assessment score of each alternative is computed in *Table 21* based on PIFWA and *Table 22* based on PIFWG.

Table 21. PIFWA-based assessment scores for each alternative.

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	$\mathbf{H_i}$
A1	0	-0.29	-0.13	-0.03	-0.13	-0.17	-0.18	-0.16	-1.0834
A2	0.29	0	0.16	0.17	0.16	0.02	0.02	0.02	0.8378
A3	0.13	-0.16	0	0.00	0.00	-0.02	-0.02	-0.02	-0.0907
A4	0.03	-0.17	0.00	0	-0.01	-0.02	-0.02	-0.02	-0.2162
A5	0.13	-0.16	0.00	0.01	0	-0.01	-0.01	-0.01	-0.0565
A6	0.17	-0.02	0.02	0.02	0.01	0	0.00	0.00	0.1980
A7	0.18	-0.02	0.02	0.02	0.01	0.00	0	0.00	0.2100
A8	0.16	-0.02	0.02	0.02	0.01	0.00	0.00	0	0.2010

Table 22. PIFWG-based assessment scores for each alternative.

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	$\mathbf{H_i}$
A1	0	-0.28	-0.03	-0.03	-0.13	-0.16	-0.18	-0.14	-0.9287
A2	0.28	0	0.16	0.16	0.03	0.02	0.02	0.02	0.6769
A3	0.03	-0.16	0	0.00	-0.01	-0.02	-0.02	-0.02	-0.1882
A4	0.03	-0.16	0.00	0	-0.01	-0.02	-0.02	-0.02	-0.1876
A5	0.13	-0.03	0.01	0.01	0	-0.01	-0.01	-0.01	0.0841
A6	0.16	-0.02	0.02	0.02	0.01	0	0.00	0.00	0.1819
A7	0.18	-0.02	0.02	0.02	0.01	0.00	0	0.00	0.2008
A8	0.14	-0.02	0.02	0.02	0.01	0.00	0.00	0	0.1609

Step 9. Sort the alternatives according to the assessment scores H_i 's decreasing values. The optimal option is the one with the highest H_i.

Table 23 presents the ranks of the alternatives concerning PIFWA and PIFWG operators.

Table 23. Rankings of the alternatives with respect to PIFWA and PIFWG operators.

Ranking	A1	A2	A3	A4	A5	A6	A7	A8
Based on PIFWA	8	1	6	7	5	4	2	3
Based on PIFWG	8	1	7	6	5	3	2	4

The best alternative is A2 based on both aggregation operators. The same alternative was the best in the proposed PSF-VIKOR method. The PSF-VIKOR method is simpler to implement and understand than PIF-CODAS. PSF-VIKOR requires less computational effort compared to PIF-CODAS, especially for problems involving a moderate number of alternatives and criteria. This makes PSF-VIKOR suitable for situations where quick decisions are necessary. Besides, PSF-VIKOR allows a broader volume to assign membership degrees, including non-membership and hesitancy degrees, whereas PIF-CODAS allows only a triangular area to assign membership and non-membership degrees. The strength of the proposed approach is its accurate and consistent membership assignment technique. The limitation of the proposed approach may appear when the experts want to assign fuzzy proportions. In this case, triangular or trapezoidal fuzzy proportions should be used for PSF-VIKOR.

5.2 | Sensitivity Analysis

In this study, determining the weights of experts has been the most challenging issue. It has been considered that basing experts' experience solely on the number of years they have worked in that field would not be entirely accurate. The differences in projects that the experts are involved in, as well as their decision-making abilities, should also be considered. Therefore, a sensitivity analysis has addressed the possibility of changes in expert weights and their potential effects on alternative rankings. *Table 24* specifies the best alternatives according to the varying expert weights.

Table 24. Best alternatives with respect to the changes in expert weights.

Experts	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7
E1	0.4	0.35	0.3	0.1	0.25	0.5	0.8
E2	0.25	0.3	0.2	0.1	0.25	0.25	0.1
E3	0.35	0.35	0.5	0.8	0.5	0.25	0.1
Best alternative	A2	A2	A2	A1, A2, A5	A2	A2	A2, A3, A7

Table 24 shows that slight changes in expert weights do not cause the best alternative to change. However, significant changes, as in Set 4 and Set 7, cause a compromise solution to be obtained. The alternatives A1, A2, and A5 are included in the compromise solution with Set 4, and the alternatives A2, A3, and A7 are included in the compromise solution with Set 7. Since alternative A2 is among the best alternatives in all sets, there should be no hesitation in selecting it. Another sensitivity analysis was conducted to see the effect of τ on alternative rankings. In our study, a value of 0.5 was recommended for τ by experts. However, whether a slight change in this value would affect the result was examined. *Table 25* presents the ranking results for values of τ ranging from 0.3-0.7.

Table 25. Rankings of the alternatives with respect to τ.

	τ				
Alternatives	0.3	0.4	0.5	0.6	0.7
A1	4	4	4	4	3
A2	1	1	1	1	1
A3	6	6	6	6	6
A4	5	5	5	5	4
A5	3	2	2	2	2
A6	7	7	7	7	7
A7	2	3	3	3	5
A8	8	8	8	8	8

6 | Conclusion

The culmination of the research presented in this paper marks a significant contribution to the field of EV evaluation, particularly focusing on the burgeoning market segment of electric SUVs and representing a significant step towards empowering consumers with informed decision-making tools in the realm of electric SUV evaluation. The development and application of the PSF-VIKOR method serve as a novel and robust approach to navigating the complex decision-making landscape inherent in selecting the most suitable electric SUV alternative, contributing to the advancement of sustainable transportation solutions and paving the way for a greener automotive future. Through a comprehensive review of existing literature and methodological advancements, this study addresses a notable gap in research by proposing a systematic framework that integrates fuzzy set theory with the VIKOR method, tailored specifically to the context of electric SUV evaluation.

The findings of this study underscore the importance of considering multiple criteria in the evaluation process, given the diverse array of factors influencing electric SUV selection. Extending the VIKOR method using PSFSs, this research accounts for the inherent vagueness and imprecision in decision-making processes. Through linguistic assessments and proportional judgments provided by domain experts, the PSF-VIKOR method offers a more intuitive and accurate means of evaluating electric SUV alternatives, encompassing criteria such as carbon footprint, operating cost, range, charging infrastructure, and performance.

However, despite the methodological advancements presented in this study, several limitations warrant consideration. Firstly, the effectiveness and generalizability of the PSF-VIKOR method may be contingent upon the quality and expertise of the individuals involved in the evaluation process. Variability in linguistic assessments and proportional judgments among experts could potentially introduce bias or inconsistency into the decision-making process. Additionally, the selection of criteria and alternatives in the electric SUV evaluation framework may not comprehensively capture the full spectrum of consumer preferences and market dynamics, thus limiting the applicability of the methodology in real-world scenarios.

The comprehensive comparative analysis conducted in this study has demonstrated the effectiveness of the PSF-VIKOR method in evaluating electric SUV alternatives compared to one of the existing methodologies, PIF-CODAS. The proposed approach not only outperformed the other method in terms of simplicity and computational efficiency but also offered greater flexibility in assigning membership degrees, thus providing decision-makers with a more intuitive and accurate evaluation framework. Additionally, the sensitivity analysis has underscored the robustness of the proposed method against variations in expert weights, ensuring consistent and reliable decision-making outcomes. These findings highlight the practical relevance and applicability of the proposed PSF-VIKOR method in navigating the multifaceted decision landscape of electric SUV selection.

Moving forward, future research endeavors should aim to address these limitations and further refine the proposed methodology. Firstly, efforts to enhance the reliability and validity of linguistic assessments within the PSF-VIKOR method could involve the development of standardized guidelines or training protocols for experts. Additionally, expanding the scope of criteria to include emerging factors such as autonomous driving capabilities, vehicle-to-grid integration, and sustainability certifications could yield a more comprehensive evaluation framework. Furthermore, comparative studies evaluating the performance of the PSF-VIKOR method against existing MCDM approaches would provide valuable insights into its efficacy and practical utility in real-world decision-making contexts.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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